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ALL SOURCE ADAPTIVE FUSION FOR AIDED NAVIGATION IN NON-GPS ENVIRONMENT

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14. ABSTRACT

An innovative approach for navigation in non-GPS environment is presented based on all source adaptive fusion of any available information encompassing passive imaging data, digital elevation terrain data, IMU/GPS, altimeters, and star tracker. The approach provides continuous navigation through non-GPS environment and yields an improved navigation in the presence of GPS. The approach also provides reduced target location error and moving target indication.

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All source adaptive fusion for aided navigation in non-GPS environnent

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ABSTRACT

An innovative approach for navigation in non-GPS environment is presented based on all source adaptive fusion of any available information encompassing passive imaging data, digital elevation terrain data, IMU/GPS, altimeters, and star tracker. The approach provides continuous navigation through non-GPS environment and yields an improved navigation in the presence of GPS. The approach also provides reduced target location error and moving target indication.

Keywords: Optical flow, GPS, target location error, structure from motion

1. BACKGROUND

There is a critical need to provide fully autonomous robust navigation capability in GPS jamming or signal interruption environment. The US Air force, Navy, and Army are keenly interested in such capability to reduce the vulnerability of GPS navigation that can be to either deliberately or unintentionally interrupted. The field of computer vision has witnessed many approaches for computing ego-motion which estimates an observer's movement (sensor or biological organism) from optical flow measurements. Optical flow is defined as "the apparent motion of the brightness patterns". The optical flow is characterized by a field of 2-D velocity vectors which are the projections of the 3-D velocity vectors of the surface points onto the image plane. The 2-D velocity vectors are derived from sequences of images. The measurement of the 2-D image velocity at a given point can be used to infer the 3-D velocity of the imaging platform. Since the optical flow is a projection of a 3-D velocity vector onto a 2-D image plane, there is an inherent ambiguity in inferring the 3-D velocity. The observed optical flow therefore needs to be fused with other measurements such as depth to remove the ambiguity and to provide an estimate of the 3-D velocity vector of the imaging platform. Knowing the observer velocity vector and the last GPS position estimate will enable, in theory, navigation in non-GPS environment. Using only optical flow measurements for navigation in non-GPS environment encounters difficulties due to the variation of depth across the image field and the presence of noise in the sequence of images. Other approaches combine precision radar sensors with digital terrain elevation databases to serve as a back-up to the GPS system. Such approaches require high-level of accuracies of digital terrain data and radar sensor.

This paper, describes an innovative approach developed by Northrop Grumman and AFRL Munitions directorate to adaptively fuse in real-time all available navigation data such as IMU/GPS, altimeters, star tracker, passive imaging sensor, and digital elevation database. The integration of passive imaging sensors has some important advantages. Foremost, the sensors are completely passive, and can operate in an environment where the GPS signal may be difficult to receive. Secondly, the sensors are immune to disruptions in the radio spectrum. The proposed approach has been implemented and demonstrated high quality navigation performance. An overview of ASAF is in section 2, and its performance is shown in section 3. Conclusions are made in section 4.

2. ALL SOURCE ADAPTIVE FUSION

The All Source Adaptive Fusion (ASAF) approach developed by Northrop Grumman and AFRL Munitions director performs at levels which are difficult to attain with single non-integrated navigation sources. Figure 1 depicts various applications of the ASAF. ASAF is a novel approach which offers the following principle advantages:

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1. Has a modular software solution which can be easily integrated on existing and future platforms;
2. Combines in real-time various sources of information as they become available (adaptive to what is available);
3. Reduces targeting error for weapon systems using EO/IR imaging sensors and provides more accurate sensor position and velocity critical to the coherent processing of the Synthetic Aperture Radar (SAR) Sensors;
4. Provides passive moving target indication (MTI); and
5. Supports both structure-from-motion (SFM) and motion-from-structure (MFS), thus providing navigation aiding in the GPS-denied environment as well as obstacle avoidance and 3-D digital terrain mapping in the presence of GPS. The 3-D digital map can be generated using ASAF software hosted on multiple surveillance UAVs flying over urban areas to provide routing support for other platforms and 3-D mapping for ground troop situation awareness.

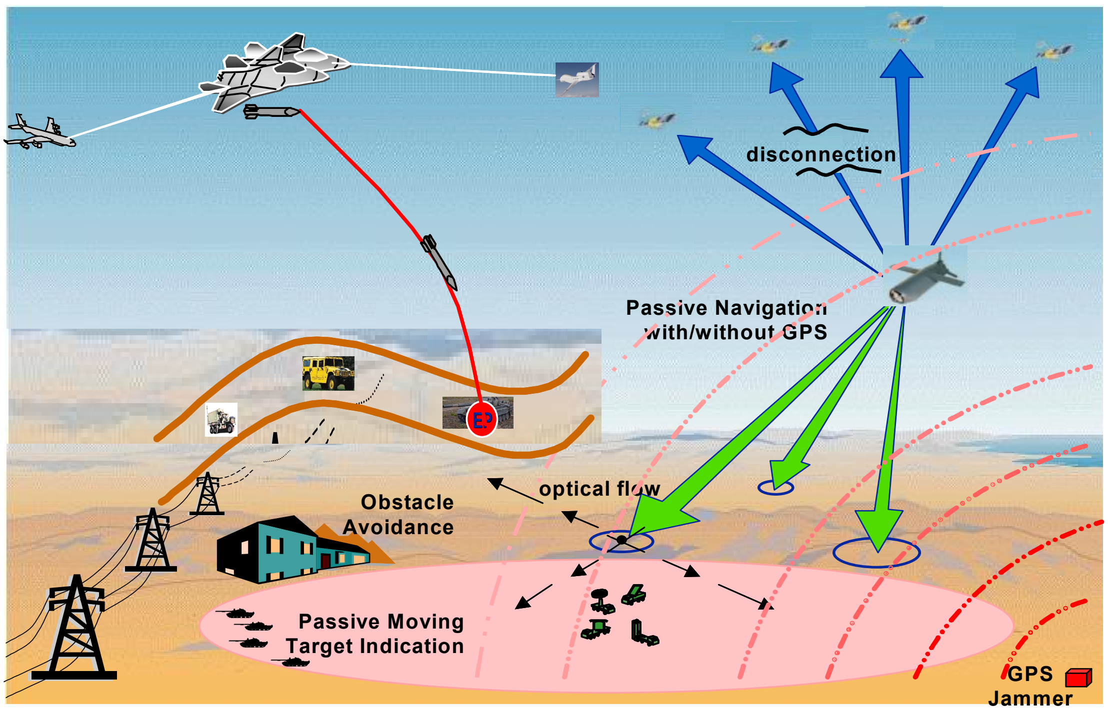

Figure 1: ASAF has wide range of applications

The major components of the ASAF are described in the following paragraphs.

2.1 Optical flow processing

Optical flow (OF) is the computation of pixel displacement or displacement velocity given a sequence of images. There are three main-stream approaches to this problem ([4]): differential, block matching and frequency methods. The differential method was based on the assumption that brightness is conserved as pixels propagate. This constraint leads to the normal flow equation, which relates the brightness gradient vector in 2D image space and brightness temporal changes in time. This equation cannot generate a unique solution and therefore needs a second constraint. Horn and Schunck built the foundation of the differential method by assuming optical flow field to change smoothly over the entire image ([1]). This assumption does not hold along occlusion boundaries and many authors have contributed to overcome this shortcoming. The variational method and its sibling modification ([3]) replace the smoothing constraint function from an identity function by a nonlinear function which suppresses smoothing on region where flow gradient is large. In other words, the weight of smoothing constraint is not uniformly distributed in the entire image, but intrinsically adjusted as part of the optimization process. The advantage of the differential method is that it produces a dense flow field.

The frequency method showed high accuracy but its computation is expensive ([4]). In the block matching method, displacement of an image block is computed based on the best match over a search neighborhood using a correlation metric. Since checking each element in the search neighborhood is slow, Lucas and Kanade proposed a steepest descent approach to speed up this process ([2]). This, together with feature selection and monitor ([5]), has formed the popular feature tracking algorithm referred to as Kanade-Lucas_Tomasi (KLT).

We have selected the KLT algorithm among a suite of optical flow algorithms to implement due to three reasons. First, since we require only a limited number of features for the subsequent fusion process (secion 2.3), knowledge of entire flow field provided by differential method is not needed. Secondly, performance evaluation literature concluded KLT is competitive in terms of accuracy and processing speed ([4]). Thirdly, experimental robots have been built using this method after independent evaluation of other approaches ([6]).

There are, however, technical challenges that KLT has not handled. First, as pointed out by other authors as well, accuracy of KLT tracking is sensitive to initial guess of displacement. This is due to the nature of steepest descent which tends to seek a nearby minimum point, regardless of whether it is a local or global minimum within the search region. For highly repeating image texture, KLT can be easily trapped by a local minimum point. Second, large displacement is handled by constructing an image pyramid and applying KLT tracking in each layer using the displacement result of upper layer as the initial guess. If the variation of feature displacement is substantial, successive initial guess by pyramid scheme will break down. Third, the feature scaling problem is not addressed. This problem may be resolved by the Scale Invariant Feature Tracking (SIFT) algorithm ([7]).

Our testbed software has implemented various optical flow algorithms including block matching and KLT algorithms. A central feature track manager is created to tightly coupled optical flow, ASAF and SFM to provide feature image position prediction. 6DOF feedback from the central fusion estimator to the optical flow and SFM was found very useful in important aircraft maneuvers as shown in section 3.1.

2.2 Structure from motion

Structure from motion (SFM) is responsible for combining Optical Flow (OF) processing with ASAF information in order to estimate the 3D positions of the features that are being tracked within an image. SFM can be thought of as somewhat of an intermediary between OF and the Navigation system, as it takes input from and provides feedback to both systems, improving the performance of each as shown in Figure 2.

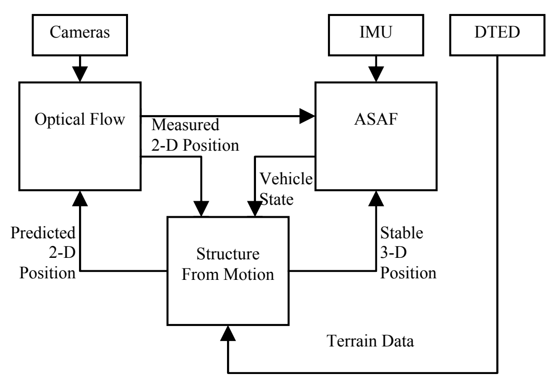

Figure 2: SFM combines optical flow processing with vehicle navigation

The 3D feature positions calculated by SFM is fed back into both the OF and ASAF modules. 3D position estimates can be used to predict 2D image locations of features, aiding OF in tracking the features. Furthermore, the tracking quality estimate of the feature can be used to aid OF in culling features that are likely being mistracked, freeing up computational resources. While to some degree the 3D location of features are already being computed implicitly within the navigation system, and as such SFM is not directly necessary, the explicit SFM system provides a number of additional benefits not available if it is left as an implicit part of Navigation.

First of all, SFM allows for an enhanced estimate of the track-quality of a given feature. Secondly, an explicit SFM dramatically increases the number of feature positions that can be estimated allowing for the construction of much denser maps. Finally, SFM allows for a more convenient and safer decoupling of features, avoiding the potential issues of system corruption that arise due to feature mistracking.

2.3 All source adaptive fusion testebed

Northrop Grumman and AFRL jointly, developed an end-to-end ASAF testbed environment for testing the overall system performance against key performance parameters. The testbed encompasses a 6-DOF simulation, physics-based scene generation tools, a suite of optical flow software, DTED, GPS/INS, and baro-altimeters. The testbed software is modular, and can be reconfigured to work in real-time mode to receive real imagery and navigation data. The ASAF module adaptively fuses in real-time all available navigation data such as IMU/GPS, altimeters, star tracker, passive imaging sensor, stored imagery, and digital elevation database. By optimally fusing all sources of data, ASAF can significantly improve navigation and targeting performance both when GPS is present and when GPS is denied as shown in section 3. ASAF software module is hosted on a Laptop computer and is a part of a flying testbed on a Cessna Grand Caravan.

3. PERFORMANCE RESULTS

The ASAF has been tested using simulated and filed data as described in the following paragraphs.

3.1 Optical flow performance

The following example illustrates the optical flow performance. The moving platform moves in a straight flight and turns with a bank angle of 20 degree. Terrain images are generated by Irma (multi-sensor signature prediction code). Terrain images represent a rural environment with random bushes and sparse buildings. Based on Irma outputs and 6DOF simulation parameters, theoretical optical flow and selected image feature position can be computed. We compared two optical flow algorithms KLT and feedback block matching as shown in Figure 3. When aircraft flies straight without acceleration, the performance of the two algorithms are comparable. But when the aircraft turns, the KLT algorithm fails completely, while the 6DOF feedback continues to maintain good performance.

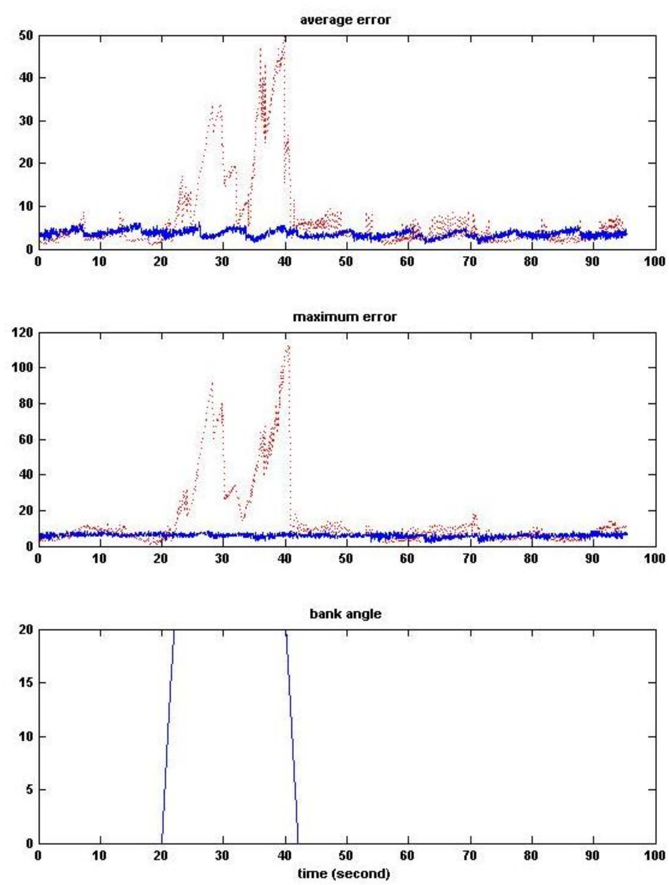

Figure 3. Optical flow performance: KLT (dotted line) and 6DOF feedback block matching algorithm (solid line)

3.2 Structure from motion performance

SFM performance was evaluated as shown in Figures 4 and 5. These results are based on a simulated vehicle flying a simple trajectory with a single camera looking straight down. Optical flow measurements are generated according to the truth model for a given feature. At generation each feature is assigned an initial true location in space and a random measurement noise value used to corrupt the feature, providing a reasonable amount of variation in feature quality. Since the image projection function is not uniquely invertible, features within SFM are initialized based on noisy a priori terrain information. Our choice of parameters in this simulation resulted in an initial error roughly ranging between 0 and 80 meters (although occasionally as large as 140 m). Figure 4 (a) demonstrates that SFM successfully combines the noisy 2D measurements from the camera into a refined 3D estimate of location. The error values for most features are nearly monotonically decreasing, and converge correctly to the true positions. It is evident from Figure 4 (a) that the error is less than 20 meters for most features by the 10th frame. Figure 4 (b) and Figure 5 additionally show the effectiveness of our Track Score calculation. We can differentiate between features with Track Score > 1 at the 10th frame. In Figure 4 (b), it is evident that the features with higher Track Scores have substantially less error than those with lower Track Scores. Furthermore, in Figure 5, it is evident that there is a strong correlation between the Track Score and both the measurement noise and the initial error. By choosing features with higher scores for use with the navigation system we can ensure that the selected features have lower measurement noise and error values, making them far more beneficial and less likely to corrupt the system.

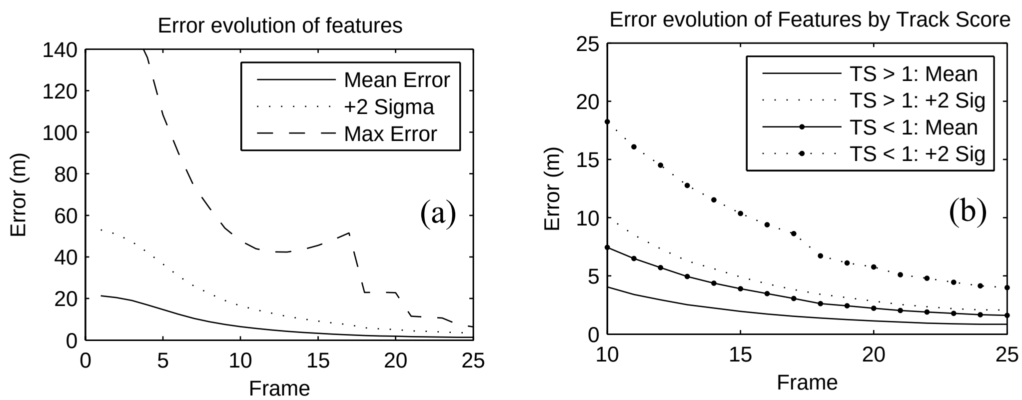

Figure 4. (a) Error between estimated feature position and true position vs. frame numbe, (b) Error vs. track score and frame number

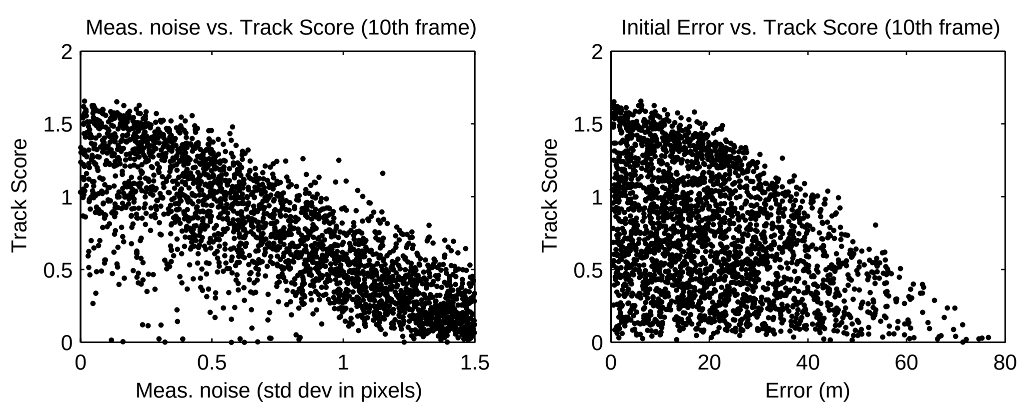

Figure 5. Computed track score, measurement noise (standard deviation in pixels of noise added to the simulated true measurement), and initial error values

3.3 ASAF navigation performance

ASAF has been tested using both simulated and real data yielding promising results. It is evident from the performance evaluation that ASAF yields an improvement over GPS only solution in the presence of GPS and provides reliable navigation aids in the non-GPS environment.

The following example illustrates the navigation performance for a navigation-grade INS/GPS. Figure 6 shows the position, heading, and velocity errors that result when GPS is lost at t = 300 sec. Figure 7 shows the same parameters, plotted to the same scale, for the case where the INS/GPS data are optimally fused with vision data starting at t = 250 sec. The imaging sensor is tracking five ground features which are known to be stationary, but whose positions are unknown.

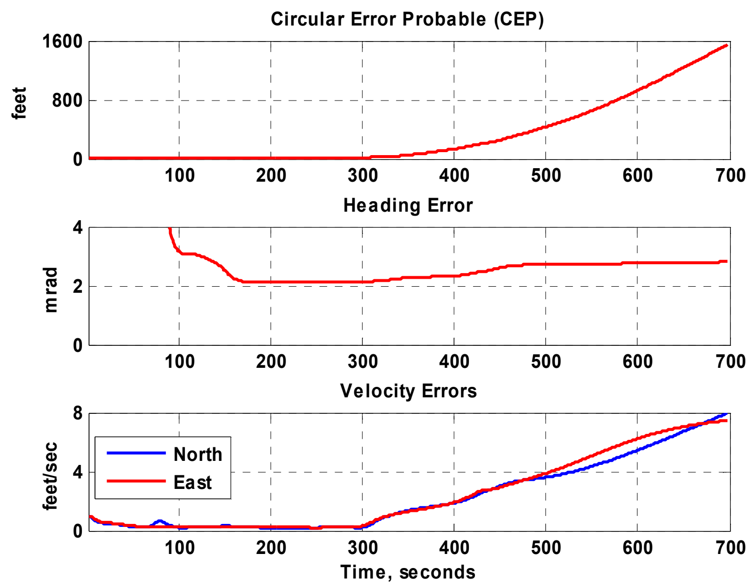

Figure 6. INS/GPS performance

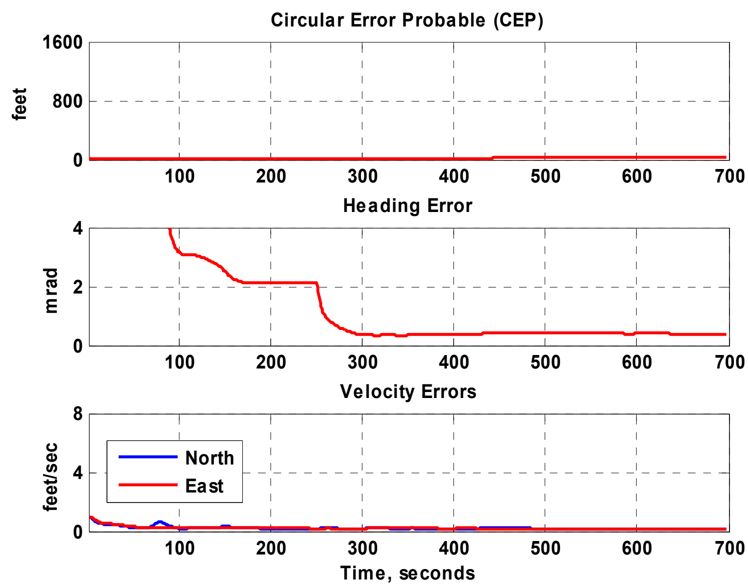

Figure 7 INS/GPS performance with optical flow aiding

The next example shows the improvement in EO/IR target location accuracy that can be obtained using ASAF. The FLIR system is assumed to have a resolution of .02 mrad and mounting tolerance plus gimbal misalignment of 1 mrad. The INS/GPS mounting tolerance and uncompensated structure flexure errors are assumed to sum to 1 mrad. A laser range finder with resolution of 1 meter is assumed available. The targeting vehicle is flying at an altitude of 20,000 feet with a look-down angle of 45 degrees. Figure 8 shows the target location errors (TLE) for INS/GPS only, compared with the results for INS/GPS plus feature tracking, again with GPS denied at t = 300 sec. Figure 9 shows the feature tracking results at an expanded scale. As shown in Figure 10, feature tracking improves TLE even when GPS is continuously available.

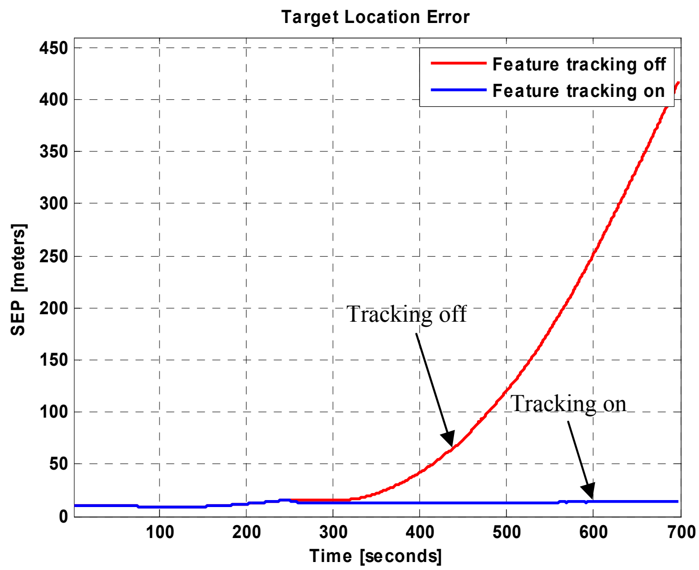

Figure 8. TLE comparison plots – GPS lost at time = 300 sec

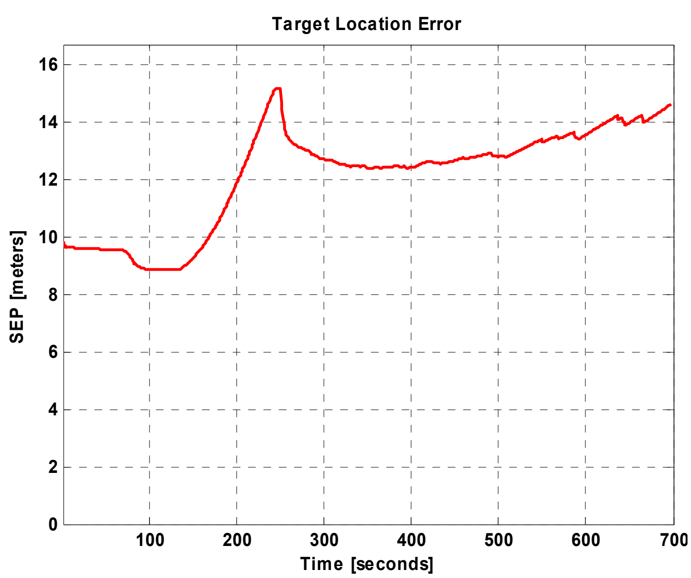

Figure 9. TLE expanded scale - feature tracking on

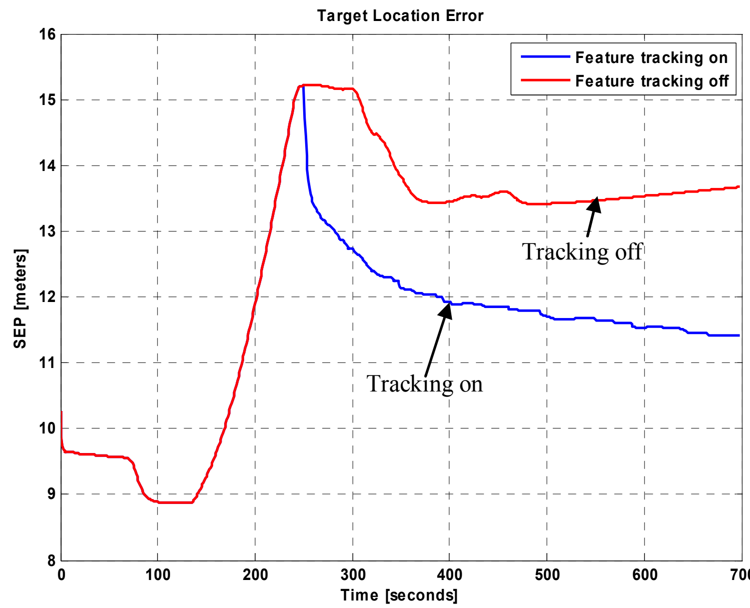

Figure 10. Comparison of TLE with and without feature tracking – GPS on

The preceding simulation results were obtained by fusing vision tracks of (unknown) discrete ground-fixed features with GPS/INS data. Table 1 shows simulation results where 2-D optical flow field velocities, rather than discrete tracks, are fused with GPS/INS data. Experiments were also run where star tracker measurements were simulated in addition to optical flow aiding. The star tracker modeled was a relatively low-precision, low-cost, miniature star tracker (3 inches x 3 inches) designed by Northrop Grumman. Two grades of INS/GPS were simulated, and two levels of optical flow measurement accuracy. It was shown that by fusing optical flow, star-tracking measurements with inertial data, navigation accuracy in a GPS-denied environment is obtained that is superior to that of INS/GPS alone when GPS is available.

Table 1. Fusion of IMU, GPS, optical flow, and star-tracker data

[1] "Inertial" = Accels + Gyros + Altimeter
[2] "Stellar-Inertial" = Inertial + Star Tracker (10 arc-sec)
[3] Includes gravity data base
[4] Registration accuracy

		CEP			
		Rate-Grade INS (LN200)		Nav-Grade INS[3] (LN250)	
Mission	Nav Mode	.1 pix[4]	.3 pix[4]	.1 pix[4]	.3 pix[4]
Smart Munition - Alt=1000 ft, V=200 ft/sec - S-curve flight path - 30 min after loss of GPS	Inertial[1]: Stellar-Inertial[2]: Inertial + Optical Flow: Stellar-Inertial + Op Flow:	16,000 500 83 17	16,000 500 108 21	3,500 138 23 13	3,500 138 28 16
Fire Scout - Alt=15,000 ft, V=200 ft/sec - 18 mile racetrack - 3 hrs after loss of GPS	Inertial: Stellar-Inertial: Inertial + Optical Flow: Stellar-Inertial + Op Flow:	40,000 310 44 30	40,000 310 180 43	16,000 303 33 21	16,000 303 50 32

4. CONCLUSIONS

The all source adaptive fusion has been implemented to fuse in real time any available information to provide fully autonomous robust navigation capability in GPS jamming or signal interruption environment. ASAF is implemented in a testbed environment to support sensitivity analysis and performance evaluation in simulated environment as well as in flight demonstration and testing using a flying Cessna Grand Caravan with mounted cameras and navigation equipment. ASAF yields superior navigation performance and can be used to reduce target location error and provide moving target indication.

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